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# Instructed motivational states bias reinforcement learning and memory formation

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**Motivation influences goals, decisions, and memory formation. *Imperative* motivation links urgent goals to actions, narrowing the focus of attention and memory. Conversely, *interrogative* motivation integrates goals over time and space, supporting rich memory encoding for flexible future use. We manipulated motivational states via cover stories for a reinforcement learning task: The imperative group imagined *executing* a museum heist, whereas the interrogative group imagined *planning* a future heist. Participants repeatedly chose among four doors, representing different museum rooms, to sample trial-unique paintings with variable rewards (later converted to bonus payments). The next day, participants performed a surprise memory test. Crucially, only the cover stories differed between the imperative and interrogative groups; the reinforcement learning task was identical, and all participants had the same expectations about how and when bonus payments would be awarded. In an initial sample and a preregistered replication, we demonstrated that imperative motivation increased exploitation during reinforcement learning. Conversely, interrogative motivation increased directed (but not random) exploration, despite the cost to participants' earnings. At test, the interrogative group was more accurate at recognizing paintings and recalling associated values. In the interrogative group, higher value paintings were more likely to be remembered; imperative motivation disrupted this effect of reward modulating memory. Overall, we demonstrate that a prelearning motivational manipulation can bias learning and memory, bearing implications for education, behavior change, clinical interventions, and communication.**

motivation | reinforcement learning | decision making | memory | reward

Memories are not veridical records of our experiences, but are instead influenced by our goals and predictions (1–3). In daily life, goals are integrated over time and space, with consequences for motivational states and for learning and memory. For example, the prospect of pleasant discoveries may motivate a hiker to explore a trail and remember many details of the experience. In contrast, if faced with a dangerous wildlife encounter, the hiker would be motivated to address or escape the threat, constraining attention and memory to goal-relevant details. Similarly, the goal of reaching the summit of a hike can supersede smaller incidental pleasures. Like threat, a reward imperative that commands single-minded attainment of an immediate goal would be expected to yield similarly sparse representations of the episode in memory. Likewise, in educational contexts, learning may be motivated by intrinsic curiosity, the desire to achieve good grades, or the fear of failure. Even objectively positive incentives can engage motivational states marked by rigidity, anxiety, or "choking under pressure," producing behavioral and memory outcomes that look similar to learning under threat (4–7). Thus, the prospect of rewards can induce distinct motivations with potential consequences for learning and memory (8, 9).

The idea that motivation influences both immediate decisions and longer term memories is intuitive. Yet, the impact of different motivational states on decision-making, memory, and the balance between these cognitive processes has yet to be demonstrated. We have proposed a theoretical framework of motivational states from which we here address these outstanding questions (10–13). According to this framework, motivational states regulating memory formation can be classified as *interrogative* or *imperative,* with both behavioral and neuromodulatory mechanisms. Interrogative motivational states are associated with broad attention and expansive information-seeking, which supports learning associations, developing cognitive maps, and, putatively, attaining future goals. Imperative motivational states are elicited by a salient, urgent goal, yielding restricted information-seeking and memory that efficiently represents predictors of the imperative goal. We posit that interrogative and imperative motivational states would have diverging consequences for memory formation due to underlying neural mechanisms (13). Whereas interrogative motivational states engage ventral tegmental area-hippocampal-prefrontal circuitry to support learning details and associations for flexible future behavior (2, 10, 14), imperative motivational states engage

## Significance

*Imperative* motivation helps us address urgent goals, such as escaping a threat or winning a competition. However, imperative motivation can constrain attention and memory. Conversely, *interrogative* motivation supports curiosity, exploration, and memory formation for future goals. Here, we tested key predictions from this theoretical framework: We varied the cover stories before a learning task to induce either imperative or interrogative motivational states, thereby influencing both reinforcement learning and subsequent memory. Our results are relevant to interventions designed to motivate immediate actions or enhance long-term memory, such as in education, behavior change, clinical practice, and science communication. Induced motivational states may shift cognitive and neural processing to support one's goals, enhancing attention, performance, learning, or memory.

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amygdala-cortical-medial temporal lobe circuitry to form sparse, decontextualized memories restricted to goal-relevant information (4, 12, 15–17).

The imperative/interrogative framework bridges ideas from past research on decision-making and emotional memory. Prior reinforcement learning studies have investigated tradeoffs between choices that *explore* options and resolve uncertainty versus choices that *exploit* reliable predictors of reward (18–24). Over a long time horizon, exploration may be more advantageous for gathering information about different options to maximize rewards over time (18); when participants have more opportunities to sample information, they engage in more exploration and make noisier choices (25). Conversely, exploitation might be the optimal approach for quickly earning rewards in a stable environment where the options are known. Balancing these strategies is important when the environment is uncertain or unstable; the optimal choice at a given time may not be the best option in the future. Prior studies on the explore/exploit tradeoff have investigated individual/group differences (20, 26, 27), used pharmacological modulation (28–30), or manipulated the number of opportunities for making choices (25), but to our knowledge have not manipulated motivational states via narrative task framing.

A separate line of research on emotional memories has contrasted positively and negatively valenced stimuli to examine consequences for memory. Strong emotions and negatively valenced stimuli can cause *memory narrowing*, which enhances memory for goal-relevant central details but impairs memory for peripheral details (15, 31–34). Likewise, stressful situations can bias decision-making, reduce behavioral flexibility, and impair learning about stimulus–outcome associations that predict threat (1, 35). The imperative/interrogative framework relates motivational states to brain states to explain how they synergistically affect information-seeking behavior and the mechanisms underlying memory formation. We predicted that imperative and interrogative motivational states would shift the balance between exploration and exploitation during reinforcement learning, while also impacting the contents and qualities of subsequent memory.

The interrogative/imperative framework generates two predictions relating goals to choice behavior and long-term memory. First, we predicted that motivational states would regulate the balance between exploration and exploitation. In reinforcement learning tasks, interrogative motivational states should encourage *directed exploration* to strategically resolve uncertainty, gather information, and develop a cognitive map (18, 23, 36). Conversely, imperative motivational states should prioritize *exploitation* to select options that reliably yield high rewards. We expected no effect of motivational state on *random exploration* (i.e., behavioral variability not aimed at resolving uncertainty) (18, 23, 36). Second, we predicted that motivational states would simultaneously bias long-term memory formation during reinforcement learning. Interrogative motivational states should enhance memory for associative details (e.g., incidental information that is associated with reward), whereas imperative motivational states should impair memory for these details (i.e., memory narrowing).

In the present study, we provide an empirical demonstration that imperative and interrogative motivational states bias reward learning and subsequent memory. Unlike previous studies which contrasted rewards and threats, in our paradigm participants completed the exact same reinforcement learning task, for the same monetary incentives. Crucially, participants had the same expectations about how bonus payments would be earned, and when those bonus payments would be awarded.

To induce imperative or interrogative motivational states during a reinforcement learning task, we introduced subtle distinctions in the cover story. Participants in the imperative condition (Sample 1: N = 99, Sample 2: N =109) were instructed to imagine *executing* a heist at an art museum (emphasizing urgent performance goals), whereas participants in the interrogative condition (Sample 1: N = 109, Sample 2: N = 111) were instructed to imagine *planning* a future heist (emphasizing learning for future goals). After reading one of the two cover stories, participants then completed a reinforcement learning task that involved searching a virtual art museum for valuable paintings (Fig. 1*A*). On each trial, participants chose one of four colored doors (representing different rooms of the museum), sampled one trial-unique painting, and learned the value of the painting (Fig. 1*B*). The underlying reward distributions associated with each door slowly drifted over the course of the experiment to encourage ongoing learning (Fig. 1*C*). The next day, participants returned to complete a surprise memory test for the paintings from the reinforcement learning task (Fig. 1*D*). Participants reported whether each painting was old or new and rated their confidence. For paintings identified as old, participants then recalled the value of the painting and the door that had been associated with the painting.

Importantly, the only difference between the two conditions was the cover story. The reinforcement learning task, the next-day memory test, and the delivery of participant payments were equated across conditions (Fig. 1*A*). Prior to the reinforcement learning task, participants in both conditions were informed that the points (painting values) earned during the task on the first day would be converted to a bonus payment that they would receive at the end of the second study session the following day. We hypothesized that imperative motivation would increase exploitation and enhance performance during reinforcement learning, but impair memory formation. Conversely, we expected that interrogative motivation would increase directed (but not random) exploration during reinforcement learning and enhance subsequent memory performance.

We collected an initial exploratory sample (Sample 1), followed by a preregistered replication sample (Sample 2). In the replication sample, we placed additional emphasis on the information about how participants could earn bonus payments, and when they would receive these earnings. In sample 1, this information was included in the consent form; in sample 2, we also emphasized this information in large text on a subsequent instruction page, presented between the consent form and the cover story. This change ensured that all participants were fully aware that the imperative and interrogative cover stories did not determine how or when performance bonuses would be awarded. The task was otherwise unchanged in sample 2. Note that because we had clear directional hypotheses for sample 2, we preregistered one-tailed statistical tests and conducted power analyses to determine sample size accordingly. Therefore, *P*-values reported are two-tailed for all sample 1 statistical tests, but one-tailed for sample 2 statistical tests with preregistered directional hypotheses (exploratory analyses in sample 2 use two-tailed tests).

## Results

**Reinforcement Learning.** First, we tested whether performance on the reinforcement learning task differed between conditions. Using linear mixed-effects regression, we predicted trial-by-trial *points* earned from *condition* (imperative vs. interrogative), including random intercepts to account for within-subject variance. During task counterbalancing, participants were randomly assigned to one of three predetermined drifting reward schedules (22); therefore, we also included a covariate of no interest for the *reward schedule*

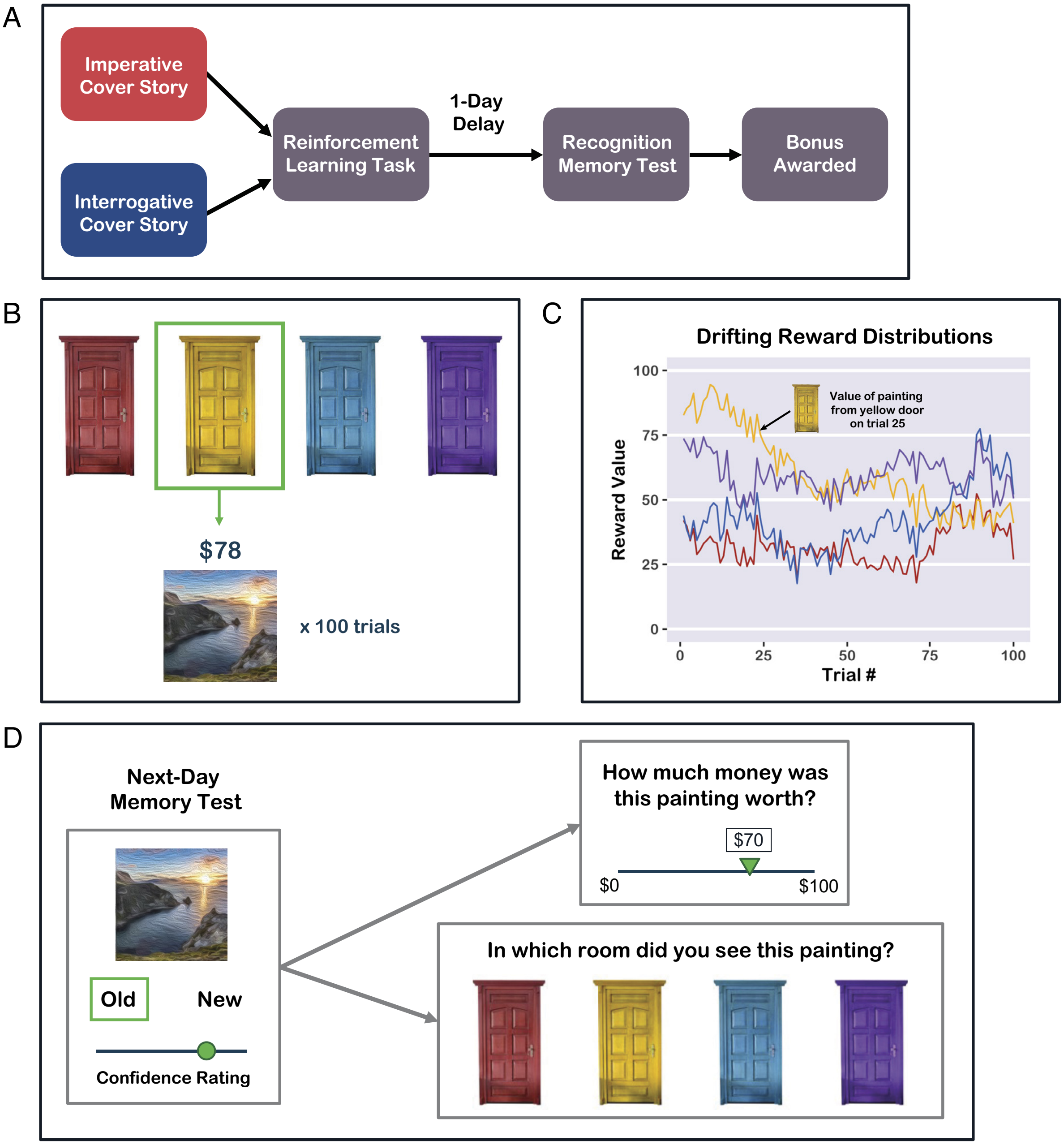


**Fig. 1.** Overview of paradigm. (*A*) Participants were randomly assigned to read either the imperative or interrogative cover story before completing a reinforcement learning task; the task was identical in both conditions. After a 1-d delay, participants returned to complete a surprise recognition memory test. Participants received their compensation and performance bonuses (earned during the reinforcement learning task) at the end of the study, regardless of condition. (*B*) On each trial of the reinforcement learning task, participants chose one of four colored doors. Participants viewed one painting sampled from the room and saw the value. (*C*) The average rewards from each of the doors drifted over time. Line colors correspond to door colors. (*D*) During the memory test, participants viewed old and new paintings and made recognition judgements with confidence ratings. For items endorsed as old, participants were also asked to recall the value of the painting and the associated door.

(version 1, 2, or 3). The model also included a covariate of no interest for the *learning trial number*, to account for fatigue or strategy changes over time.

In both samples, participants in the imperative condition earned more points than participants in the interrogative condition (sample 1: $\beta$ = 0.07, 95% CI [0.03, 0.11], $t$ = 3.39, two-tailed $P$ < 0.001; sample 2: $\beta$ = 0.06, 95% CI [0.03, 0.10], $t$ = 3.63, one-tailed $P$ < 0.001). We also tested a generalized linear mixed-effects model with *optimal choices* as the dependent variable (i.e., binary variable indicating whether or not the participant chose the door with the highest value). Imperative condition participants made more optimal choices than interrogative condition participants (sample 1: $\beta$ = 0.15, 95% CI [0.06, 0.24], $z$ = 3.24, two-tailed $P$ = 0.001; sample 2: $\beta$ = 0.08, 95% CI [0.00, 0.16], $z$ = 1.89, one-tailed $P$ = 0.029).

We also conducted two control analyses to ensure that participants successfully learned from feedback (*SI Appendix, Evidence of Reinforcement Learning*). First, we tested whether the number of optimal choices for each participant was greater than chance (chance performance would be 25/100 trials, if participants chose among the four doors randomly). In both samples, we observed that the number of optimal choices was well above chance in both conditions. Second, we tested whether trial-by-trial reward feedback influenced subsequent choices. In both conditions, we found that greater rewards increased the likelihood of repeating the previous choice, in both samples. Further information about these analyses is provided in *SI Appendix*, *Evidence of Reinforcement Learning*. Taken together, these two control analyses provide convergent evidence that participants in both conditions successfully engaged in reinforcement learning. Overall, we found that participants in the imperative condition earned more points (Fig. 2*A*) and made more optimal choices during reinforcement learning (Fig. 2*B*), though participants in both conditions successfully performed the reinforcement learning task.

We then compared choice behavior across the two conditions by using reinforcement learning models. We developed eight different computational models to fit trial-by-trial choice behaviors in the reinforcement learning task using hierarchical Bayesian modeling (*Methods*, *Computational Modeling*). Each model was comprised of a learning rule that governed how participants updated the expected value of the chosen door after observing a reward on a given trial (learning rate), and a choice rule that integrated various kinds of value estimates that may influence choices (reward-based expected value, uncertainty-based directed exploration bonus, and choice history-based perseveration bonus).

We compared two learning rules: 1) a delta learning rule that updates expected value of the chosen door by a constant learning rate on every trial and 2) a Bayesian learning rule that updates expected value by a learning rate proportional to the trial-by-trial estimated uncertainty of the chosen door. Each learning rule was combined with one of four choice rules. The first choice rule included an *inverse temperature* parameter to model *exploitation*, the tendency to select doors based on expected values to maximize reward gained. The second choice rule added an additional parameter for *perseveration*, the tendency to repeat the choice made on the previous trial. The third choice rule consisted of an *inverse temperature* parameter and a parameter for *directed exploration*, the tendency to sample doors with high estimated uncertainty to gather information and resolve uncertainty. The fourth choice rule included both additional parameters for *perseveration* and *directed exploration*. Model comparison results showed that the model with a delta learning rule and the fourth choice rule (including parameters for inverse temperature, directed exploration, and perseveration) had the highest predictive accuracy, outperforming all other models (*SI Appendix*, Fig. S1).

Using the best-fitting model, we tested whether trial-by-trial choices differed between conditions. For each participant, we extracted model-derived expected reward values (Fig. 3*A*) and uncertainty values (Fig. 3*B*) for each door on each trial, and classified each choice based on whether it was *exploitation* (choosing the door with the highest expected value), *directed exploration* (choosing the door with the highest uncertainty), or *random exploration* (choosing one of the other two doors). In order to make pairwise comparisons between conditions for each choice category (exploitation, directed exploration, and random exploration), we conducted three separate Wilcoxon rank sum tests (a nonparametric alternative to two-sample $t$ tests since the

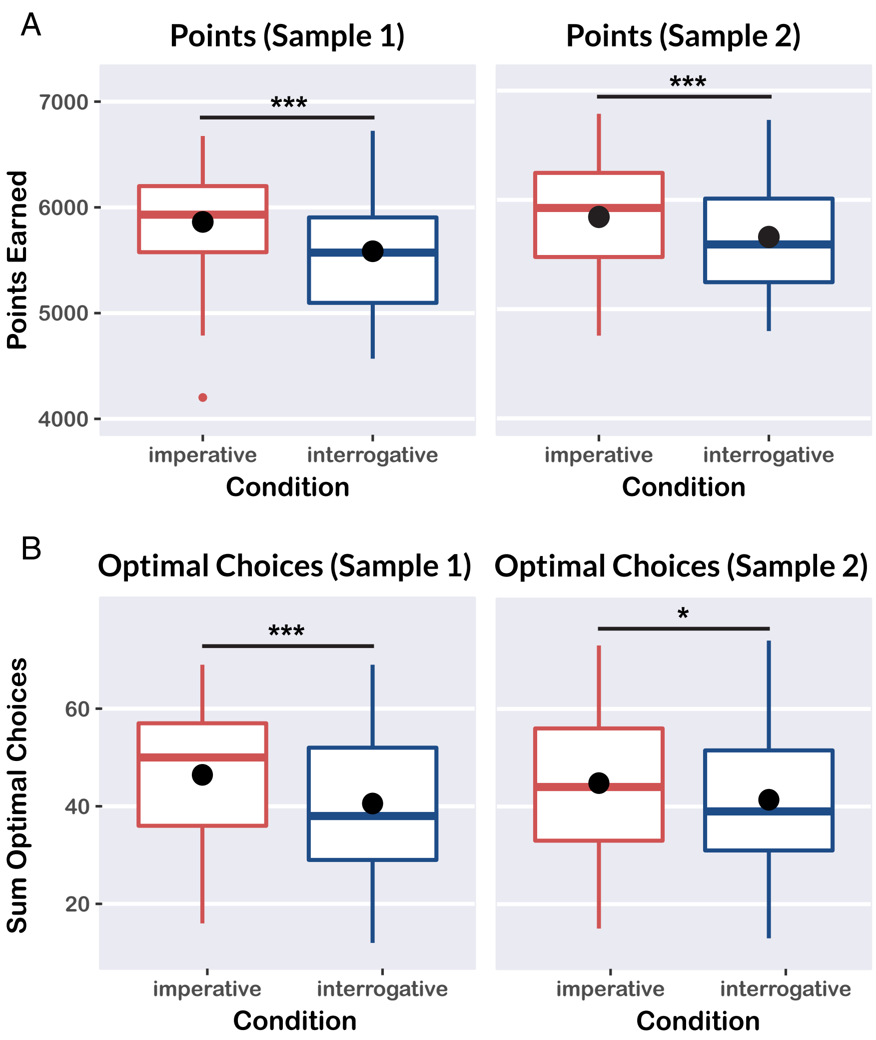


**Fig. 2.** Comparing reinforcement learning performance across conditions. Boxplots depict data distributions (center line = median; box limits = upper and lower quartiles; whiskers = 1.5× interquartile range; outer points = outliers; center points = mean). In both samples, participants in the imperative condition earned more points (*A*) and made more optimal choices (*B*) than participants in the interrogative condition. *$P$ < 0.05, ***$P$ < 0.001.

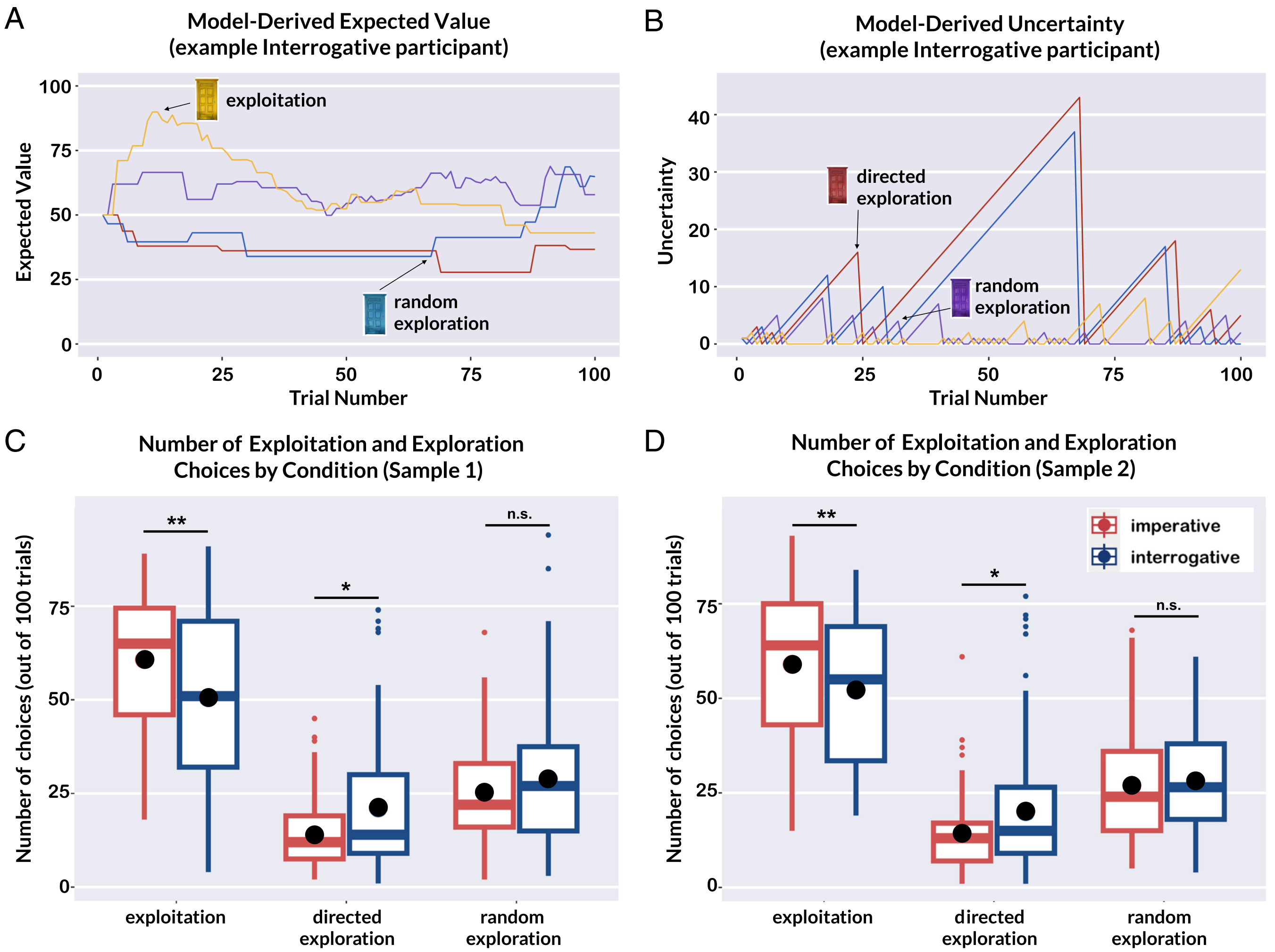


**Fig. 3.** Model-derived classification of choices. Lines depict trial-by-trial expected value (*A*) and uncertainty (*B*) for each of the four doors (line colors correspond to door colors) for one example interrogative participant. Arrows note example trials classified as "exploitation" (highest expected value), "directed exploration" (highest uncertainty), and "random exploration" (neither highest expected value nor highest uncertainty). Group differences by choice type are shown in *C* and *D*. Box-and-whisker plots show choice distributions (center line = median; box limits = upper and lower quartiles; whiskers = 1.5× interquartile range; outer points = outliers; center points = mean; error bars = SEM). In both samples, participants in the imperative condition made more exploitation choices, whereas participants in the interrogative condition made more directed exploration choices. *$P < 0.05$. **$P < 0.01$.

normality assumption was violated) to predict *number of choices* for each choice type, respectively, from *condition* (imperative vs. interrogative).

In both samples, participants in the imperative condition made more exploitation choices (sample 1: W = 6326.6, two-tailed $P = 0.001$, Cohen's $d = 0.50$, 95% CI [0.22, 0.78]; sample 2: W = 7272.5, one-tailed $P = 0.005$, Cohen's $d = 0.34$, 95% CI [0.08, 0.61]) and fewer directed exploration choices (sample 1: W = 4,001, two-tailed $P = 0.015$, $d = -0.51$, 95% CI [−0.80, −0.23]; sample 2: W = 4,954, one-tailed $P = 0.010$, $d = -0.44$, 95% CI [−0.70, −0.17]) compared to participants in the interrogative condition (Fig. 3 *C* and *D*). As predicted, the number of random exploration choices did not differ between conditions (sample 1: W = 4,400, two-tailed $P = 0.215$, $d = -0.24$, 95% CI [−0.52, 0.04]; sample 2: W = 5,458, two-tailed $P = 0.252$, $d = -0.08$, 95% CI [−0.34, 0.19]). These differences in choice behavior across imperative and interrogative conditions were confirmed by results from multinomial logit regressions (*SI Appendix*, Tables S1 and S2).

Note that in the reinforcement learning task, choosing among the four doors was self-paced. In contrast, the feedback page (displaying the painting and associated reward value) was presented for a fixed duration. In exploratory analyses, we examined whether choice reaction time differed across conditions and choice types (exploitation, directed exploration, and random exploration). Reaction time analyses are reported in *SI Appendix, Reaction Time*; there were no replicable differences in reaction time.

Next, we compared the imperative and interrogative conditions in terms of group-level learning measures. We examined the effect of condition on reinforcement learning based on the estimated group mean difference hyperparameter posterior distribution for the key learning rule parameter *learning rate* (Dα). Individual differences in this learning rate parameter reflect differences in sensitivity to prediction error (i.e., how much one adjusts expectations in response to feedback). Whereas the trial-level choice type analysis above allowed us to compare the number of exploitation and exploration choices made by participants in the imperative and interrogative conditions, the group difference hyperparameter posterior distribution pools uncertainty across all the trials and across all participants within each condition to provide an overall estimate of how reward learning tendencies—namely how much participants learned from observed prediction errors to adjust their reward expectations for subsequent trials—differed between conditions.

In sample 1, compared to those in the interrogative condition, participants in the imperative condition had a significantly higher *learning rate*; the 95% highest density continuous interval of the posterior distribution of the group difference hyperparameter (Dα) was positive and did not overlap with 0 (Sample 1: 95% CI [0.0553, 0.1851]; Fig. 4*A*). This effect was weaker in sample 2, where the 95% interval of the posterior distribution was mostly positive but did overlap with 0 (Sample 2: 95% CI [−0.0113, 0.1122]; Fig. 4*B*). In other words, participants in the imperative condition tended to be more sensitive to prediction error, though this effect was stronger in sample 1 than in sample 2.

We also took the same approach to examine the effect of condition on three key choice rule parameters in the model: *inverse temperature* ($D_\beta$), *directed exploration* ($D_{\varphi\phi}$), and *perseveration* ($D_\rho$; *SI Appendix*, Fig. S2). In both samples, the group-level results for inverse temperature and directed exploration were generally consistent with the trial-level choice type analyses reported above; imperative group participants tended to show more exploitation during reinforcement learning, whereas interrogative group participants tended to show more directed exploration. As the trial-level analyses offer similar but more sensitive measures of exploitation and directed exploration, we report the group-level analyses in *SI Appendix*. Additionally, we found that as expected, there was no group differences in the perseveration parameter, which reflects participants' tendencies to repeat choices over time.

Overall, participants in the imperative condition earned more points, made more optimal choices, and made more exploitation choices during reinforcement learning. Conversely, participants in the interrogative group earned fewer points, made fewer optimal choices, and made more directed exploration choices. In sample 1, we also found that participants in the imperative condition showed higher learning rates than participants in the interrogative condition; this effect was in the expected direction in sample 2, but weaker and nonsignificant.

**Recognition Memory.** Next, we examined performance on the next-day memory test. Using generalized linear mixed-effects regression, we compared trial-by-trial *recognition accuracy* (0 = incorrect, 1 = correct) for paintings (including both old stimuli and novel lures) across *conditions* (Imperative vs. Interrogative). The model included covariates of no interest for the *reward schedule* (version 1, 2, or 3) and the duration of the *delay* (in hours) between the learning session and test session (all were overnight delays, approximately 24 h between learning and test). The model included random intercepts to account for within-subject variance. In both samples, recognition accuracy was significantly higher in the interrogative condition than in the imperative condition (sample 1: $\beta = -0.08$, 95% CI [−0.13, −0.04], $z = -3.48$, two-tailed $P < 0.001$; sample 2: $\beta = -0.04$, 95% CI [−0.08, −0.01], $z = -2.01$, one-tailed $P = 0.022$) (Fig. 5 *A* and *B*).

We then modified the model described above to investigate reward modulation of memory, focusing on old stimuli. In addition to the parameters described in the model above, we included parameters for *reward* (continuous variable, the value associated with a painting during the learning phase) and the interaction between *reward* and *condition* (imperative vs. interrogative). We also added a covariate of no interest for the *learning trial number*, accounting for potential fatigue or primacy effects (note that this variable was not included in the previous model because it could not be applied to new stimuli). We predicted that reward would enhance memory, but imperative motivation would disrupt this effect.

In both samples, reward significantly enhanced recognition memory for the paintings (sample 1: $\beta = 0.07$, 95% CI [0.04, 0.11], $z = 4.00$, two-tailed $P < 0.001$; sample 2: $\beta = 0.03$, 95% CI [0.00, 0.06], $z = 1.83$, one-tailed $P = 0.034$). Crucially, this effect of reward enhancing memory depended on condition. In both samples, there were significant interactions between reward and condition (sample 1: $\beta = -0.04$, 95% CI [−0.07, −0.001], $z = -2.05$, two-tailed $P = 0.040$; sample 2: $\beta = -0.03$, 95% CI [−0.06, −0.001], $z = -1.77$, one-tailed $P = 0.038$).

As expected, follow-up tests indicated that reward significantly enhanced memory in the interrogative condition (sample 1: $\beta = 0.11$, $z = 4.39$, two-tailed $P < 0.001$; sample 2: $\beta = 0.06$, $z = 2.58$, one-tailed $P = 0.005$), but not in the imperative condition (sample 1: $\beta = 0.04$, $z = 1.34$, two-tailed $P = 0.175$; sample 2: $\beta = 0.001$, $z = 0.05$, two-tailed $P = 0.960$). In other words, high-value items were prioritized in memory, but only under an interrogative motivational state (Fig. 6). All other parameter estimates are reported in *SI Appendix*, Tables S3 and S4.

In a supplemental analysis, we also investigated whether recognition accuracy, condition, choice type, and reward were related to confidence ratings provided during the memory test.

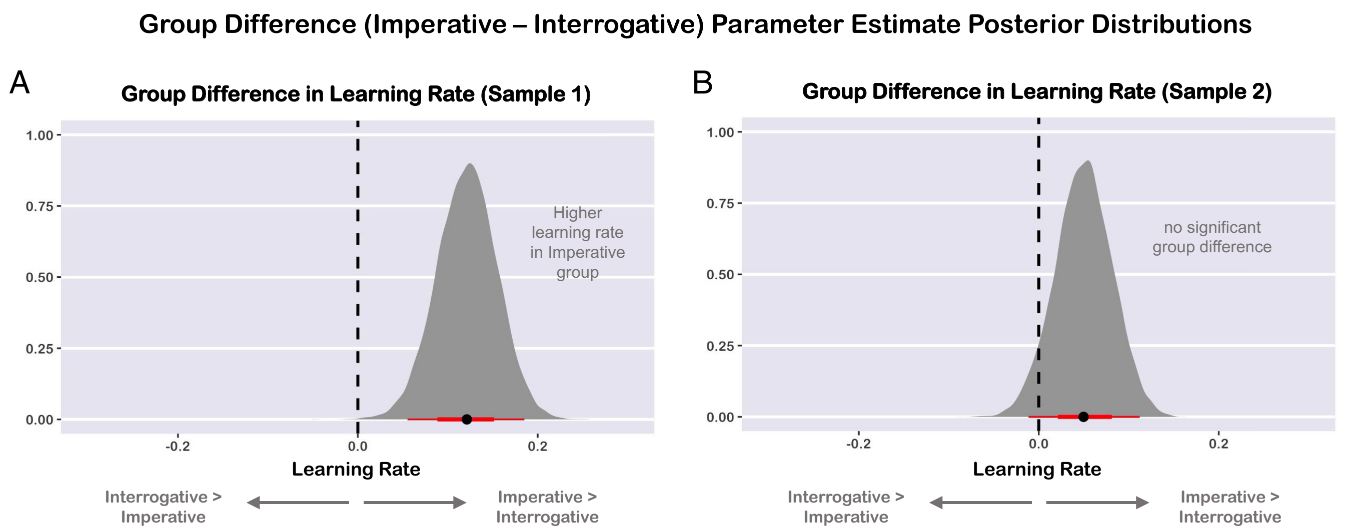


**Fig. 4.** Group difference (imperative condition – interrogative condition) hyperparameter posterior distributions for learning rate (Dα) of the best-fitting model. The black dots represent the mean, thick red lines the 80% highest density continuous intervals, and thin red lines the 95% intervals. Dashed black lines represent 0 (i.e., no difference between conditions). In sample 1, learning rate was higher in the imperative condition than the interrogative condition (*A*), but this effect was not significant in sample 2 (*B*).

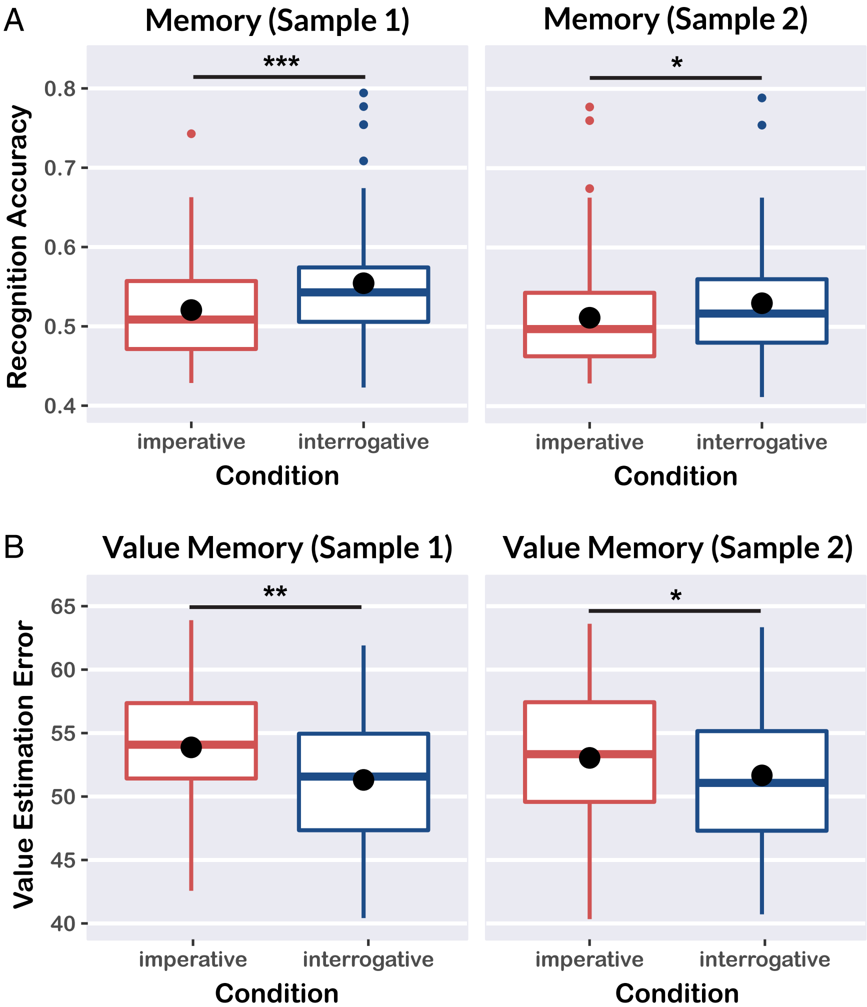


**Fig. 5.** Memory outcomes across conditions. Boxplots depict data distributions (center line = median; box limits = upper and lower quartiles; whiskers = 1.5× interquartile range; outer points = outliers; center points = mean). In both samples, participants in the interrogative condition were significantly more accurate at recognizing paintings (*A*) and recalling associated values (*B*) on the next-day memory test. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.



Participants were more confident in correct responses, but there were no other significant effects (*SI Appendix, Recognition Memory Confidence*).

Last, we also tested variants of the mixed-effects model described above to explore whether memory outcomes were related to individual differences in choice behavior (inverse temperature, directed exploration, perseveration, and learning rate) or trial-wise estimates of prediction error. There were no reliable effects depending on these parameters. These exploratory analyses are reported in detail in *SI Appendix, Relating Reinforcement Learning Parameters to Memory* and Tables S5–S8).

**Corrected Recognition.** Next, we investigated subject-level corrected recognition scores ($d'$). First, we used one-sample $t$ tests to check whether corrected recognition was above chance performance. Average corrected recognition scores ($d'$) were well above chance (0) in both the imperative condition (sample 1: M = 0.34, $t(82) = 7.96$, $P < 0.001$, Cohen's $d = 0.87$, 95% CI [0.62, 1.13]; sample 2: M = 0.27, $t(104) = 6.91$, $P < 0.001$, Cohen's $d = 0.67$, 95% CI [0.46, 0.89]) and in the interrogative condition (Sample 1: M = 45.6, $t(74) = 9.01$, $P < 0.001$, Cohen's $d = 1.04$, 95% CI [0.76, 1.33]; sample 2: M = 0.39, $t(97) = 8.82$, $P < 0.001$, Cohen's $d = 0.89$, 95% CI [0.66, 1.13]).

Second, we used linear regression to test whether average corrected recognition scores differed between conditions. This model included covariates of no interest for the reward schedule and delay to test. In both samples, there was weak evidence that $d'$ scores tended to be higher in the interrogative condition than the imperative condition (Sample 1: $\beta = -0.15$, 95% CI [−0.31, 0.02], $t = -1.79$, two-tailed $P = 0.075$; sample 2: $\beta = -0.15$, 95% CI [−0.29, 0.00], $t = -1.97$, two-tailed $P = 0.050$). Note that this analysis is less sensitive than the trial-wise recognition memory analyses reported previously; $d'$ scores for each subject were calculated across trials.

**Associative Memory.** Next, we examined memory for painting–value associations. Using linear mixed-effects regression, we predicted trial-by-trial *value estimation error*, defined as the discrepancy between estimated and actual values (for paintings correctly identified as "old"), from *condition* (imperative vs. interrogative). The model included covariates of no interest for the reward schedule, delay duration, and learning trial number (to account for potential fatigue or primacy effects), as well as random intercepts for subjects. In both samples, participants in the interrogative condition were more accurate at recalling painting–value associations (Fig. 5 *C* and *D*); error scores were lower than in the imperative condition (sample 1: $\beta = 0.06$, 95% CI [0.01, 0.10], $t = 2.64$, two-tailed $P = 0.009$; sample 2: $\beta = 0.05$, 95% CI [0.01, 0.09], $t = 3.00$, one-tailed $P = 0.011$).

Last, we modified the model described above to conduct an exploratory analysis, predicting trial-by-trial accuracy for scene–door associations. There were no significant differences between the imperative and interrogative conditions in either sample 1 ($\beta = -0.06$, 95% CI [−0.18, 0.06], $z = -0.95$, two-tailed $P = 0.340$)

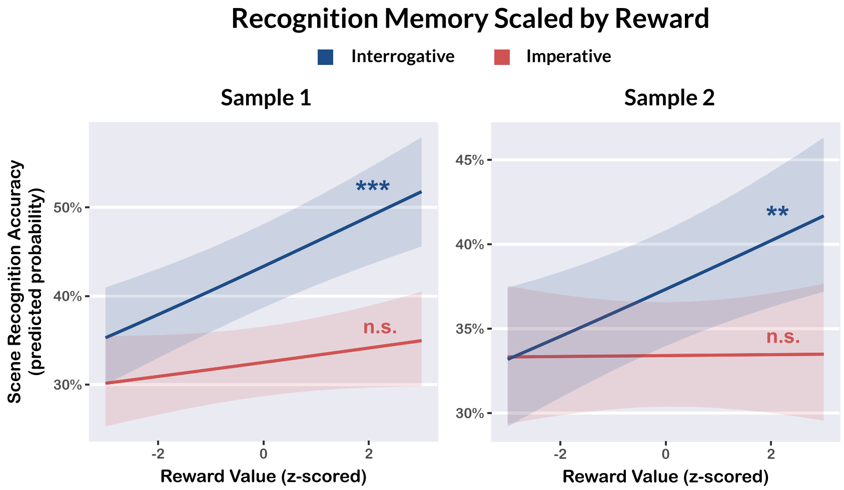


**Fig. 6.** Recognition memory was scaled by reward. Shaded bands indicate 95% CIs. Lines depict slope estimates from mixed-effects models predicting trial-wise recognition accuracy for old paintings. In the interrogative condition, reward modulated memory, such that high-value paintings were more likely to be remembered than low-value paintings. In contrast, this expected effect of reward on memory was eliminated in the imperative condition. This interaction effect replicated in sample 2. $^{**}P < 0.01$, n.s. = not significant.



or sample 2 ($\beta = -0.01$, 95% CI [−0.12, 0.11], $z = -0.11$, two-tailed $P = 0.913$). However, overall memory for painting–door associations was very poor (sample 1: M = 14.4%, sample 2: M = 13.3%), limiting our ability to detect potential effects on associative memory.

## Discussion

In two samples, we demonstrated that a prelearning motivational manipulation influenced reinforcement learning and subsequent memory. We used cover stories to manipulate motivational states before a reinforcement learning task with trial-unique stimuli. Participants in the imperative condition were instructed to imagine *executing* an art museum heist, whereas participants in the interrogative condition were instructed to imagine *planning* a future heist. Importantly, only the cover stories differed across conditions; all participants completed the exact same reinforcement learning task for the same monetary incentives. Participants in both conditions were aware that their bonus payments would be determined by points earned during the reinforcement learning task.

Participants in the imperative condition tended to make more exploitative choices and earn more points during the reinforcement learning task. Conversely, participants in the interrogative condition tended to make more directed exploration choices, despite the cost to their own earnings. The next day, we conducted a surprise memory test to assess recognition memory for trial-unique paintings previously shown during the reinforcement learning task. Participants in the interrogative condition demonstrated better recognition memory and recall for associated values, as well as an effect of reward enhancing memory for high-value paintings. Conversely, participants in the imperative condition were less accurate, and showed no effect of reward modulating memory. We validated our key findings in a preregistered replication sample. Overall, we conclude that imperative and interrogative motivational states bias choice behavior and memory formation in divergent ways, aligning cognitive processes with current goals.

**Motivational States Influence Reinforcement Learning.** Results from the reinforcement learning task demonstrated that the cover stories influenced choice behavior. Model-free analyses of reinforcement learning performance showed more exploitative tendencies in the imperative condition, as participants in the imperative condition earned more points and made more optimal choices during reinforcement learning in both samples. These results were consistent with model-based analyses of choice type. Using trial-by-trial values derived from reinforcement learning models, we identified *exploitation* choices (choosing to maximize reward) and *directed exploration* choices (choosing to resolve uncertainty). We found robust evidence that participants in the imperative condition made more exploitative choices and participants in the interrogative condition made more directed exploration choices; this finding was evident in both samples. In sample 1 we also observed that participants in the imperative group were more sensitive to prediction error (i.e., making larger adjustments to reward expectations in response to feedback), but this effect was weaker and nonsignificant in sample 2.

Exploitation and directed exploration were inversely related in our data, but these measures are not redundant. Model comparison demonstrated that including a separate parameter for directed exploration tendencies accounted for additional variance in choice behavior that was not explained by exploitation alone (*SI Appendix*, Fig. S1). Importantly, directed exploration also contrasted with random exploration (choosing a door that was neither highest-value nor highest-uncertainty) in our trial-level choice analysis: Random exploration did not differ between the imperative and interrogative conditions in either sample. Although participants in the interrogative condition were instructed to "explore the museum to plan a future heist," they showed a specific increase in directed exploration, not random exploration. In contrast, prior research has shown that increasing the time horizon of information seeking generally invigorates exploration and increases choice variance (25). Our results suggest that, rather than increasing general behavioral variability or invigorating exuberance, the interrogative cover story specifically motivated information seeking to resolve uncertainty about the environment.

**Interrogative Motivation Enhances Memory Formation.** The interrogative and imperative cover stories also influenced incidental memory of trial-unique paintings viewed during the reinforcement task. Importantly, the paintings were irrelevant to the reinforcement learning task; participants in both the imperative and interrogative conditions were aware that choosing among *doors* was important for obtaining rewards, whereas the specific paintings viewed did not inform choices. On a next-day memory test, participants in the interrogative condition showed significantly higher recognition accuracy for the paintings. In sample 2, we also observed that participants in the interrogative condition were more accurate at recalling the values associated with specific paintings.

Our results indicate that interrogative motivation enhanced memory formation, whereas imperative motivation disrupted the effects of reward on memory. For participants in the interrogative condition, reward prioritized items in memory; high-value paintings were more likely to be remembered, and low-value paintings were less likely to be remembered. This effect of reward modulating memory has been demonstrated in many prior studies (2, 14, 37). Strikingly, participants in the imperative condition did not show the expected effect of reward, corroborating our prior work (4, 10). This evidence that imperative motivational states can disrupt reward modulation of memory offers an important caveat for incentivizing learning in daily life (e.g., offering rewards for good grades).

The reward enhancement of memory effect we observed in the interrogative condition relates to prior behavioral and neural evidence that reward can automatically enhance episodic memory, independent of encoding strategy (38–41). Prior behavioral work has shown that memory for high-value items is enhanced even when the memory test itself is unrewarded (42). In our paradigm, the interrogative cover story led participants to think about planning for future rewards— this "planning" orientation aligns with prior evidence that midbrain dopamine mediates value-driven enhancement of memory, regardless of intentions to learn (2, 40). Similarly, other studies have shown that the hippocampus supports planning in multistep reward learning tasks (43, 44), and VTA neurons fire in anticipation of rewards (45, 46).

Overall, we found that imperative motivation increased exploitative choices during reinforcement learning, enhancing short-term performance while impairing memory formation. Conversely, interrogative motivation increased directed exploration and enhanced memory formation, particularly for information associated with reward. Crucially, participants in the interrogative condition made more exploratory choices and formed lasting memories, despite the personal cost of reducing their own reward earnings. The tradeoff between task performance and memory outcomes in the imperative and interrogative conditions aligns with prior research on the complementarity of reinforcement learning and episodic memory systems (47–50). We propose that imperative and interrogative motivational states offer distinct benefits for short-term reward learning and longer term memory retention.

**Imperative and Interrogative States Support Distinct Goals.** Imperative and interrogative motivational states have advantages and disadvantages in different situations (11, 12, 16). Imperative motivation can support maximizing reward, escaping or confronting threats, or addressing urgent needs. However, imperative motivation can induce a narrow focus for attention and memory, thus producing sparse, decontextualized memories that are susceptible to overgeneralization (51, 52). Conversely, an interrogative motivational state can support future planning, flexible reconfiguration of knowledge, and drawing inferences. With a broader and less constrained focus, one can encode more information, learn associations, or develop a cognitive map. The imperative/interrogative theoretical framework unifies evidence from distinct literatures; prior studies have separately shown that manipulating task contexts (e.g., high- vs. low-reward incentives, reward vs. threat, gains vs. losses, stealing vs. buying, or single vs. sequential choices) can elicit different patterns in choice behavior, neural responses, skin conductance, and subsequent memory (10, 25, 50, 53–60).

The imperative/interrogative framework (11, 12) also unifies some elements of the explore/exploit tradeoff with prior studies on *promotion* and *prevention* goals (61) and emotional memory. Promotion goals drive individuals to seek beneficial outcomes, whereas prevention goals motivate action to avoid negative outcomes. Framing risky decision-making tasks in terms of gains or losses can elicit differences in choice behavior (55, 62–64) and neural activation (65–67). Separately, research on emotional memories has demonstrated that strong emotions and negatively valenced stimuli can cause *memory narrowing*, prioritizing memory for goal-relevant central details while impairing memory for peripheral details (15, 31–34). Only a few studies have investigated goal framing effects on memory formation (10, 68), one of which is our prior demonstration that prevention goal framing (perhaps inducing an imperative motivational state) disrupted an expected relationship between encoding and retrieval.

Other prior studies have manipulated participants' perspectives, such as by instructing participants to read a story from the perspective of a burglar or a prospective home buyer (60). These differing perspectives can influence attention and encoding (60), as well as later recall (69) (i.e., shifting perspectives during recall prioritizes retrieval of distinct details). Our paradigm was distinct from these prior studies because participants were not explicitly instructed or incentivized to memorize information; the manipulation of motivational states was separate from participants' personal motivation to earn bonus payments. Future versions of our paradigm could vary whether participants think about stealing or buying, whether the goal is to earn rewards or avoid punishment, and whether outcomes are urgent or distant.

Synthesizing these disparate lines of research offers several theoretical advances. The imperative/interrogative framework: 1) captures the diverse effects of motivation on learning, decision-making, *and* subsequent memory, 2) draws on neuromodulatory evidence (11–13) to elucidate tradeoffs between neural systems for immediate action and elaborated memory formation, and 3) transcends the dichotomy between positive and negative stimuli or outcomes. For example, this framework explains memory outcomes better than theories that consider emotional valence alone (15). An imperative motivational state can be driven by either punishments or rewards, leading to avoidance or compulsive behavior, respectively. Conversely, morbid curiosity is an example of interrogative motivation to learn about negatively valenced information (70, 71). The imperative/interrogative framework offers a perspective by bridging prior research in reinforcement learning, decision-making, and emotional memory, thus generating predictions for brain and behavior.

**Limitations and Future Directions.** Future research could build on our results by testing additional predictions of the imperative/interrogative framework. One prediction that we were unable to test is that interrogative motivation supports drawing inferences and applying memories to serve flexible future goals. In the present study, we showed that interrogative motivation enhanced recognition memory and associative memory for incidental information (paintings) paired with rewards. A key goal for future research is to test whether interrogative motivation supports generalization, inference, or adaptive memory updating, as predicted. For example, recent work has shown that reward reorganizes and clusters related memories, which may support flexible future use (72). A related prediction is that interrogative motivation may influence how the hippocampus integrates or differentiates between related stimuli, supporting adaptive memory (73). In ongoing work, we are investigating the neural correlates of choices and subsequent memory with this paradigm; fMRI data would enable investigation of hippocampal patterns.

Another limitation is that we employed a reinforcement learning task that involved reward probabilities that slowly drift over time; this necessitates ongoing learning and balancing exploration/exploitation strategies. However, the drifting rewards did not fully align with the cover story presented in the interrogative condition; planning a heist is difficult if one knows that rewards fluctuate over time. The present study also does not test reversal learning that occurs when reward contingencies suddenly change dramatically. In future research, task variations with fixed reward schedules or blocked designs could offer additional insight into the effects of imperative and interrogative motivation.

Additionally, the present study only tested memory after a 24-h delay. We chose this delay period to permit memory consolidation—behavioral effects of reward on memory sometimes only emerge after a delay that permits consolidation (74, 75), likely because reward has been shown to enhance hippocampal replay during rest (76). We demonstrate that the effects of motivation and reward are evident after a delay that permits consolidation, but we were not able to determine whether these effects *require* consolidation. Future studies could test shorter or longer delay periods to investigate when these memory effects emerge.

In our paradigm, we instructed participants to "imagine" being a thief as they moved through a museum, discovering art within rooms that varied in value. The only difference in imagination requirements between conditions was the reason for the activity: reconnaissance versus implementation. Although we did not instruct participants to construct mental imagery or visualize specific details, some participants may have spontaneously generated mental imagery. As there are substantial individual differences in the ability to conjure mental imagery (77, 78), it is possible that individuals who form more detailed mental images may respond more to our instructional manipulation. For instance, in prior research, we showed that an imagination exercise enhanced subsequent learning from prediction error pertaining to health risks (79). Future studies could investigate whether individual differences in mental imagery predict the extent to which our cover stories influence behavioral indices of motivational states.

Similarly, our findings relate to other literatures that pertain to planning and future-oriented cognition. Prior studies have shown that imagination (episodic simulation and episodic future thinking) can encourage patient decision-making (80, 81) and enhance prospective memory (82, 83). Engaging episodic memory systems via imagination may thus increase future-oriented thinking and interrogative motivation. Future studies that involve episodic simulation could explore whether the vividness of imagined scenarios predicts motivation, exploration, or memory outcomes.

**Conclusion.** By using a prelearning manipulation of motivational states, we biased participants' choice behavior and memory outcomes. Imperative motivation promoted exploitative choices to maximize rewards during reinforcement learning, whereas interrogative motivation promoted directed exploration to reduce uncertainty. Interrogative motivation enhanced subsequent recognition, reward prioritization, and value memory, whereas imperative motivation disrupted reward enhancements of memory. These findings have broad theoretical implications; the imperative/interrogative motivational framework unifies and reconciles findings from memory and decision-making research. Instructed motivational states could strategically prioritize immediate performance or long-term learning, thus aligning cognitive processes with learning goals to support context-appropriate choices and memory formation.

## Methods

**Participants.** The study was approved by the Duke University Campus Institutional Review Board (protocol #2022-0032). We collected an initial sample (sample 1), then validated our findings in a preregistered replication sample (sample 2). In sample 1, we recruited 200 participants from Prolific, an online testing platform. This sample size was chosen to exceed the samples previously reported in similar paradigms (23, 28), account for attrition, and ensure an adequate amount of data for using hierarchical computational modeling to estimate group differences in latent variables. Data collection for sample 1 was conducted in two batches; we collected additional data to supplement an initial sample after observing effects of interest with small effect sizes. For sample 2, we conducted a power analysis based on key results from sample 1 (*SI Appendix*, *Power Analyses*). We then preregistered a replication sample with directional hypotheses. After exclusions and attrition (*SI Appendix*, *Exclusions and Attrition*), sample 1 included 200 participants (158 with Session 2 data) and sample 2 included 220 participants (200 with session 2 data).

Participants were compensated with \$2.50 for completing session 1 (approximately 15 min) and \$3 for completing session 2 (approximately 20 min). We also calculated bonus payments determined by points earned during the session 1 reinforcement learning task (average bonus = \$5). During the recruitment and consent process, participants were informed that the bonus would be determined by performance during the reinforcement learning task, but this bonus would not be awarded until after completion of the entire two-session study.

All participants were young adults (mean age 28.1 y, range 19 to 36 y). The gender identity (self-reported) distribution was balanced (49.6% female, 49.6% male, 0.8% other/not disclosed). The racial distribution was as follows: 58.8% White, 17.6% Asian, 9.7% Black, 9.2% two or more races, and 3.7% other. Inclusion criteria were as follows: fluent in English, currently residing in the United States, no current psychiatric or neurological diagnoses, no current medication use to treat psychiatric conditions, and normal or corrected-to-normal vision. Participants provided informed consent via an online form presented before the task.

**Imperative and Interrogative Conditions.** All participants completed a task that involved searching a virtual art museum for valuable paintings. Although the task and reinforcement contingencies were identical for the two conditions, the imperative and interrogative conditions featured different task instructions that varied the cover story, thus influencing participants' motivational states. In the imperative condition, participants were instructed to imagine that they were a master thief executing a heist at an art museum (emphasizing urgent, salient goals). In the interrogative condition, participants read a slightly different version of the cover story that instructed them to imagine that they were a master thief scouting the museum to plan a future heist (emphasizing exploration for future goals). The full text of these cover stories is provided in *SI Appendix*, *Cover Story Text*. Participants were randomly assigned to either the imperative condition (sample 1: $n = 99$, sample 2: $n = 109$) or the interrogative condition (sample 1: $n = 101$, sample 2: $n = 111$).

Importantly, all participants were informed (in the advertisement and consent form) that they would receive a performance bonus that depended on points earned during the art museum task, but this bonus would not be awarded until they returned the following day and completed the second study session. Therefore, expectations about actual reward contingencies and delivery were equated across conditions. Since the interrogative cover story emphasized planning for future goals, one concern is that interrogative condition participants may have been confused about whether they would directly benefit from points earned during the art museum task, or whether they would need to revisit the art museum the following day to earn a bonus. To ensure that participants in both conditions fully understood the bonus payments, in sample 2 we added a clarification message after the consent form to emphasize that bonus payments would be determined by the points earned during the art museum task in session 1, and bonuses would not be awarded until after completion of session 2. Participants in sample 2 were required to press a button to acknowledge this clarification message.

**Art Museum Task (Reinforcement Learning).** Participants completed 100 trials of an online 4-armed restless bandit task (programmed with PsychoPy v2021.2.3 and hosted by Pavlovia) in which they searched a virtual art museum for valuable paintings. On each trial (self-paced), the participant chose one of four colored doors (i.e., bandits), representing different rooms of the museum. The participant then viewed one trial-unique painting sampled from the room, with the value of the painting displayed below the image (4 s). After a brief fixation screen (1.5 s), participants returned to the four doors to begin the next trial. The stimuli were 100 unique scene images edited with an Adobe Photoshop filter that mimicked the appearance of a painting. The order of the paintings presented was randomized for each subject. The paintings themselves were irrelevant to the reinforcement learning task; the goal was to choose among the four doors to either maximize rewards (imperative condition) or learn about the average value of the doors (interrogative condition).

Each room of the museum yielded rewards drawn from a different value distribution. The average reward from each room drifted slowly over the course of the task to encourage ongoing learning and exploration. To ensure that effects were not specific to a particular reward schedule, participants were randomly assigned to one of three drifting reward schedules, the same schedules used in two prior studies (23, 28). The mean rewards for each door followed decaying Gaussian random walks (decay parameter $\lambda = 0.9836$; decay center $\theta = 50$). On each trial, the reward value was drawn from the distribution for the chosen door with mean payoff $\mu_{i,t}$ and variance $\sigma_o^2 = 4^2$ (observation variance) and diffused with noise drawn from a distribution with $\mu = 0$ and $\sigma_d^2 = 2.8^2$ (diffusion variance).

The task also included attention checks to ensure participant engagement. Between trials (after the fixation screen), participants sometimes viewed an image of a museum security guard (2 s) and were instructed to press the spacebar key to avoid the guard. There was a 10% chance of the guard appearing on any given trial. On average, participants successfully completed 11.29 attention checks.

**Next-Day Memory Test.** The next day, participants were asked to return for a second session that consisted of a self-paced memory test. Prior to returning for session 2, participants were not informed that there would be a memory test. Across both samples, the average delay between sessions was 25 h (range 19 to 45 h). In sample 1, the final sample for the memory test consisted of 158 participants (imperative: n = 83, interrogative: n = 75). In sample 2, the final sample for the memory test consisted of 200 participants (imperative: n = 105, interrogative: n = 95).

We presented 100 paintings previously shown during the art museum task and 75 novel paintings in a randomized order. Due to a programming error, the stimulus set used for the memory test included two similar images of the same landmark; these two trials were excluded from analyses for each participant. On each trial, participants viewed one painting image, reported whether it was old or new, and rated their confidence on a continuous sliding scale with anchors at zero ("Guessing") and one ("Very confident"). For paintings identified as "old," participants were subsequently asked to report the value of the painting and identify the museum door that had been associated with the painting during the reinforcement learning task.

**Computational Modeling.** We developed eight hierarchical Bayesian reinforcement learning models to fit trial-by-trial choice behavior. Each model consisted of a *learning rule* that governed the rate of expected value update after observing the reward outcome on a trial, and a *choice rule* that integrated various kinds of value estimates. In each model, all free parameters at the participant level were estimated hierarchically, and we modeled a group difference hyperparameter to account for potential difference in means between the imperative and interrogative conditions (see *Model Fitting* section in *SI Appendix* for more details).

All models were estimated using hierarchical Bayesian modeling in the RStan package (84) (version 2.21.0) in R (version 4.1.2) with data from sample 1. After parameter estimation, we used Bayesian leave-one-out cross-validation approximation to compare the predictive accuracy of the eight models using the *loo* package (85) (version 2.4.1). The *loo* package uses Pareto smoothed importance sampling (PSIS) to compute pointwise out-of-sample predictive accuracy, where one data point (observed choice on one trial) is repeatedly taken out of the dataset and how well the refitted model (refitted on the remaining data) predicts the left-out data point is estimated. PSIS-loo values were calculated for each model based on the fitted RStan output, using the log likelihood function evaluated at the sampled posterior parameter values. PSIS-loo values are not biased in favor of more complex models (28, 86). Model comparison results showed that the model with the Delta learning rule and the choice rule with all three components (expected value + directed exploration bonus + perseveration bonus) had the highest predictive accuracy (*SI Appendix*, Fig. S1). Parameter estimates from the best-fitting model were used in subsequent behavioral analyses for both samples.

Briefly, the best-fitting model included the following free parameters: a learning rate parameter $\alpha$, an inverse temperature parameter $\beta$, a directed exploration parameter $\varphi$, and a perseveration parameter $\rho$. The *learning rate* controls the proportion of the prediction error (difference between expected value and observed reward) used in updating expected value, and is the same across all trials in the delta learning rule. According to the choice rule, door choices are made based on three factors: The *inverse temperature* parameter controls the extent to which a participant chooses based on the expected value of the doors, the *directed exploration* parameter controls the extent to which a participant chooses to resolve uncertainty about the expected value (uncertainty is proportional to the amount of time since a door was last chosen; refs. 21 and 28), and the *perseveration* parameter controls the extent to which a participant repeats the choice they made on the previous trial.

Further information about model specifications, model fitting procedure, model checks and validation are provided in *SI Appendix* (sections entitled *Model Specification, Model Fitting, Prior Predictive Checks, Model Recovery, Parameter Recovery, and Posterior Predictive Checks*; *SI Appendix*, Figs. S3–S6). Stan code for all models is provided in an Open Science Framework repository (https://osf.io/7sz23/).

**Statistical Analyses.** Statistical analysis was conducted with R; further information about packages is provided in *SI Appendix* (*R Packages*). For sample 1, all statistical tests reported were two-tailed. For sample 2, we preregistered directional hypotheses and conducted one-tailed tests. Significance testing for all mixed-effects models used Satterthwaite approximations of degrees of freedom.

Based on the trial-by-trial estimated values and uncertainties for each door produced by the best-fitting model, we classified each choice as *exploitation* (selecting the door with the highest expected value), *directed exploration* (selecting the door with the highest uncertainty), or *random exploration* (selecting one of the other doors) (23, 28). Each postwarmup iteration of model-fitting generated trial-by-trial expected value estimates for each door (the expected values for each door before a choice was made on a given trial), and the mean values from all iterations were used as the model-estimated expected value in the choice classification analysis. Uncertainty in the delta learning rule model was operationalized as the number of trials since a door was last selected (21, 28).

**Data, Materials, and Software Availability.** All data and code necessary to reproduce results are provided in a permanent, publicly accessible repository hosted by the Open Science Framework (https://osf.io/7sz23/) (87). Sample 1 was not preregistered. Sample 2 was a preregistered replication sample (https://osf.io/ftqkr) (88).

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1. C. A. Hartley, E. A. Phelps, Anxiety and decision-making. *Biol. Psychiatry* **72**, 113–118 (2012).
2. D. Shohamy, R. A. Adcock, Dopamine and adaptive memory. *Trends Cogn. Sci.* **14**, 464–472 (2010).
3. K. C. Dickerson, M. R. Delgado, Contributions of the hippocampus to feedback learning. *Cogn. Affect Behav. Neurosci.* **15**, 861–877 (2015).
4. V. P. Murty, K. S. LaBar, D. A. Hamilton, R. A. Adcock, Is all motivation good for learning? Dissociable influences of approach and avoidance motivation in declarative memory. *Learn. Mem.* **18**, 712–717 (2011).
5. D. Ariely, U. Gneezy, G. Loewenstein, N. Mazar, Large stakes and big mistakes. *Rev. Econ. Stud.* **76**, 451–469 (2009).
6. D. Mobbs *et al.*, Choking on the money: Reward-based performance decrements are associated with midbrain activity. *Psychol. Sci.* **20**, 955–962 (2009).
7. R. Yu, Choking under pressure: The neuropsychological mechanisms of incentive-induced performance decrements. *Front. Behav. Neurosci.* **9**, 19 (2015).
8. M. Reindl, M. Tulis, M. Dresel, Profiles of emotional and motivational self-regulation following errors: Associations with learning. *Learn. Individ. Differ.* **77**, 101806 (2020).
9. M. R. Lepper, J. H. Corpus, S. S. Iyengar, Intrinsic and extrinsic motivational orientations in the classroom: Age differences and academic correlates. *J. Educ. Psychol.* **97**, 184–196 (2005).
10. K. S. Chiew *et al.*, Motivational valence alters memory formation without altering exploration of a real-life spatial environment. *PLoS One* **13**, e0193506 (2018).
11. K. C. Dickerson, R. A. Adcock, "Motivation and memory" in *Stevens' Handbook of Experimental Psychology and Cognitive Neuroscience, Learning and Memory*, (John Wiley & Sons, 2018), pp. 215–242.
12. V. P. Murty, R. A. Adcock, "Distinct medial temporal lobe network states as neural contexts for motivated memory formation" in *The Hippocampus from Cells to Systems: Structure, Connectivity, and Functional Contributions to Memory and Flexible Cognition*, (Springer International Publishing, 2017), pp. 467–501.

13. K. S. Chiew, R. A. Adcock, "Motivated memory: Integrating cognitive and affective neuroscience" in *The Cambridge Handbook of Motivation and Learning*, Cambridge Handbooks in Psychology, K. A. Renninger, S. E. Hidi, Eds. (Cambridge University Press, 2019), pp. 517–546.
14. R. A. Adcock, A. Thangavel, S. Whitfield-Gabrieli, B. Knutson, J. D. E. Gabrieli, Reward-motivated learning: Mesolimbic activation precedes memory formation. *Neuron* **50**, 507–517 (2006).
15. D. Clewett, V. P. Murty, Echoes of emotions past: How neuromodulators determine what we recollect. *eNeuro* **6**, ENEURO.0108-18.2019 (2019).
16. V. P. Murty, K. C. Dickerson, "Motivational influences on memory" in *Recent Developments in Neuroscience Research on Human Motivation*, Advances in Motivation and Achievement (Emerald Group Publishing Limited, 2016), pp. 203–227.
17. V. P. Murty, K. S. LaBar, R. A. Adcock, Distinct medial temporal networks encode surprise during motivation by reward versus punishment. *Neurobiol. Learn. Mem.* **134**, 55–64 (2016).
18. R. C. Wilson, E. Bonawitz, V. D. Costa, R. B. Ebitz, Balancing exploration and exploitation with information and randomization. *Curr. Opin. Behav. Sci.* **38**, 49–56 (2021).
19. J. D. Cohen, S. M. McClure, A. J. Yu, Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration. *Philos. Trans. R. Soc. B Biol. Sci.* **362**, 933–942 (2007).
20. M. A. Addicott, J. M. Pearson, M. M. Sweitzer, D. L. Barack, M. L. Platt, A primer on foraging and the explore/exploit trade-off for psychiatry research. *Neuropsychopharmacology* **42**, 1931–1939 (2017).
21. M. Speekenbrink, E. Konstantinidis, Uncertainty and exploration in a restless bandit problem. *Topics Cogn. Sci.* **7**, 351–367 (2015).
22. P. Domenech, S. Rheims, E. Koechlin, Neural mechanisms resolving exploitation-exploration dilemmas in the medial prefrontal cortex. *Science* **369**, eabb0184 (2020).
23. N. D. Daw, J. P. O'Doherty, P. Dayan, B. Seymour, R. J. Dolan, Cortical substrates for exploratory decisions in humans. *Nature* **441**, 876–879 (2006).
24. K. Nussenbaum, Novelty and uncertainty differentially drive exploration across development. PsyArXiv [Preprint] (2022), 10.31234/osf.io/pkn7j (Accessed 14 July 2022).
25. R. C. Wilson, A. Geana, J. M. White, E. A. Ludvig, J. D. Cohen, Humans use directed and random exploration to solve the explore-exploit dilemma. *J. Exp. Psychol. Gen.* **143**, 2074–2081 (2014).
26. A. Wiehler, K. Chakroun, J. Peters, Attenuated directed exploration during reinforcement learning in gambling disorder. *J. Neurosci.* **41**, 2512–2522 (2021).
27. H. Sadeghiyeh *et al.*, Temporal discounting correlates with directed exploration but not with random exploration. *Sci. Rep.* **10**, 4020 (2020).
28. K. Chakroun, D. Mathar, A. Wiehler, F. Ganzer, J. Peters, Dopaminergic modulation of the exploration/exploitation trade-off in human decision-making. *ELife* **9**, e51260 (2020).
29. M. Jepma, E. Te Beek, E.-J. Wagenmakers, J. Van Gerven, S. Nieuwenhuis, The role of the noradrenergic system in the exploration-exploitation trade-off: A pharmacological study. *Front. Hum. Neurosci.* **4**, 170 (2010).
30. M. Dubois *et al.*, Human complex exploration strategies are enriched by noradrenaline-modulated heuristics. *ELife* **10**, e59907(2021).
31. L. J. Levine, R. S. Edelstein, "Emotion and memory narrowing: A review and goal-relevance approach" in *Cognition and Emotion* (Psychology Press, 2010).
32. J. M. Fawcett, E. J. Russell, K. A. Peace, J. Christie, Of guns and geese: A meta-analytic review of the 'weapon focus' literature. *Psychol. Crime Law* **19**, 35–66 (2013).
33. M. Mather, Emotional arousal and memory binding: An object-based framework. *Perspect. Psychol. Sci.* **2**, 33–52 (2007).
34. M. Mather, M. R. Sutherland, Arousal-biased competition in perception and memory. *Perspect. Psychol. Sci.* **6**, 114–133 (2011).
35. C. M. Raio, C. A. Hartley, T. A. Orederu, J. Li, E. A. Phelps, Stress attenuates the flexible updating of aversive value. *Proc. Natl. Acad. Sci. U.S.A.* **114**, 11241–11246 (2017).
36. S. J. Gershman, Uncertainty and exploration. *Decision* **6**, 277–286 (2019).
37. E. A. Miendlarzewska, D. Bavelier, S. Schwartz, Influence of reward motivation on human declarative memory. *Neurosci. Biobehav. Rev.* **61**, 156–176 (2016).
38. M. S. Cohen, J. Rissman, M. Hovhannisyan, A. D. Castel, B. J. Knowlton, Free recall test experience potentiates strategy-driven effects of value on memory. *J. Exp. Psychol. Learn. Mem. Cognit.* **43**, 1581–1601 (2017).
39. M. S. Cohen, L. Y. Cheng, K. A. Paller, P. J. Reber, Separate memory-enhancing effects of reward and strategic encoding. *J. Cogn. Neurosci.* **31**, 1658–1673 (2019).
40. B. J. Knowlton, A. D. Castel, Memory and reward-based learning: A value-directed remembering perspective. *Annu. Rev. Psychol.* **73**, 25–52 (2022).
41. B. L. Elliott, C. Blais, S. M. McClure, G. A. Brewer, Neural correlates underlying the effect of reward value on recognition memory. *NeuroImage* **206**, 116296 (2020).
42. C. R. Madan, M. L. Spetch, Is the enhancement of memory due to reward driven by value or salience? *Acta Psychol.* **139**, 343–349 (2012).
43. I. Momennejad, A. R. Otto, N. D. Daw, K. A. Norman, Offline replay supports planning in human reinforcement learning. *ELife* **7**, e32548 (2018).
44. I. Momennejad, Learning structures: Predictive representations, replay, and generalization. *Curr. Opin. Behav. Sci.* **32**, 155–166 (2020).
45. L. M. Ferguson, A. M. Ahrens, L. G. Longyear, J. W. Aldridge, Neurons of the ventral tegmental area encode individual differences in motivational "wanting" for reward cues. *J. Neurosci.* **40**, 8951–8963 (2020).
46. A. E. Kosobud, G. C. Harris, J. K. Chapin, Behavioral associations of neuronal activity in the ventral tegmental area of the rat. *J. Neurosci.* **14**, 7117–7129 (1994).
47. G. E. Wimmer, E. K. Braun, N. D. Daw, D. Shohamy, Episodic memory encoding interferes with reward learning and decreases striatal prediction errors. *J. Neurosci.* **34**, 14901–14912 (2014).
48. A. M. Bornstein, M. W. Khaw, D. Shohamy, N. D. Daw, Reminders of past choices bias decisions for reward in humans. *Nat. Commun.* **8**, 1–9 (2017).
49. K. Foerde, E. K. Braun, D. Shohamy, A trade-off between feedback-based learning and episodic memory for feedback events: Evidence from Parkinson's disease. *Neurodegener. Dis.* **11**, 93–101 (2013).
50. G. M. Rosenbaum, H. L. Grassie, C. A. Hartley, Valence biases in reinforcement learning shift across adolescence and modulate subsequent memory. *ELife* **11**, e64620 (2022).
51. J. E. Dunsmoor, V. P. Murty, L. Davachi, E. A. Phelps, Emotional learning selectively and retroactively strengthens memories for related events. *Nature* **520**, 345–348 (2015).
52. E. E. Bernstein, F. van der Does, S. P. Orr, R. J. McNally, Poor mnemonic discrimination predicts overgeneralization of fear. *J. Psychopathol. Behav. Assess* **43**, 152–161 (2021).
53. M. R. Delgado, V. A. Stenger, J. A. Fiez, Motivation-dependent responses in the human caudate nucleus. *Cereb. Cortex* **14**, 1022–1030 (2004).
54. M. A. Niznikiewicz, M. R. Delgado, Two sides of the same coin: Learning via positive and negative reinforcers in the human striatum. *Dev. Cogn. Neurosci.* **1**, 494–505 (2011).
55. S. Fiedler, A. Hillenbrand, Gain-loss framing in interdependent choice. *Games Eco. Behav.* **121**, 232–251 (2020).
56. E. H. Limbrick-Oldfield, R. Leech, R. J. S. Wise, M. A. Ungless, Financial gain- and loss-related BOLD signals in the human ventral tegmental area and substantia nigra pars compacta. *Eur. J. Neurosci.* **49**, 1196–1209 (2018).
57. V. P. Murty, K. S. LaBar, R. A. Adcock, Threat of punishment motivates memory encoding via amygdala, not midbrain, interactions with the medial temporal lobe. *J. Neurosci.* **32**, 8969 (2012).
58. K. R. Mickley, E. A. Kensinger, Emotional valence influences the neural correlates associated with remembering and knowing. *Cogn. Affect. Behav. Neurosci.* **8**, 143–152 (2008).
59. D. V. Smith, K. E. Sip, M. R. Delgado, Functional connectivity with distinct neural networks tracks fluctuations in gain/loss framing susceptibility. *Hum. Brain Mapping* **36**, 2743–2755 (2015).
60. J. W. Pichert, R. C. Anderson, Taking different perspectives on a story. *J. Educ. Psychol.* **69**, 309–315 (1977).
61. D. C. Molden, A. Y. Lee, E. T. Higgens, "Motivations for promotion and prevention" in *Handbook of Motivation Science*, (Guilford Press, 2008), pp. 169–187.
62. D. Kahneman, A. Tversky, "Prospect theory: An analysis of decision under risk" in *Handbook of the Fundamentals of Financial Decision Making*, World Scientific Handbook in Financial Economics Series (World Scientific, 2012), pp. 99–127.
63. A. Tversky, D. Kahneman, Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertain.* **5**, 297–323 (1992).
64. N. C. Barberis, Thirty years of prospect theory in economics: A review and assessment. *J. Eco. Perspect.* **27**, 173–196 (2013).
65. C. Trepel, C. R. Fox, R. A. Poldrack, Prospect theory on the brain? Toward a cognitive neuroscience of decision under risk. *Cogn. Brain Res.* **23**, 34–50 (2005).
66. C. R. Fox, R. A. Poldrack, "Prospect theory and the brain," in *Neuroeconomics*, P. W. Glimcher, C. F. Camerer, E. Fehr, R. A. Poldrack, Eds. (Academic Press, 2009), pp. 145–173.
67. C. Gonzalez, J. Dana, H. Koshino, M. Just, The framing effect and risky decisions: Examining cognitive functions with fMRI. *J. Eco. Psychol.* **26**, 1–20 (2005).
68. S. R. Touryan *et al.*, The influence of self-regulatory focus on encoding of, and memory for, emotional words. *Soc. Neurosci.* **2**, 14–27 (2007).
69. R. C. Anderson, J. W. Pichert, Recall of previously unrecallable information following a shift in perspective. *J. Verbal Learn. Verbal Behav.* **17**, 1–12 (1978).
70. S. Oosterwijk, Choosing the negative: A behavioral demonstration of morbid curiosity. *PLoS One* **12**, e0178399. (2017).
71. C. Scrivner, The psychology of morbid curiosity: Development and initial validation of the morbid curiosity scale. *Pers. Individ. Differ.* **183**, 111139 (2021).
72. E. A. Horwath, N. Rouhani, S. DuBrow, V. P. Murty, Value restructures the organization of free recall. PsyArXiv [Preprint] (2022). https://doi.org/10.31234/osf.io/2ah3d (Accessed 16 May 2022).
73. I. K. Brunec, J. Robin, R. K. Olsen, M. Moscovitch, M. D. Barense, Integration and differentiation of hippocampal memory traces. *Neurosci. Biobehav. Rev.* **118**, 196–208 (2020).
74. K. Murayama, S. Kitagami, Consolidation power of extrinsic rewards: Reward cues enhance long-term memory for irrelevant past events. *J. Exp. Psychol. Gen.* **143**, 15–20 (2014).
75. A. Patil, V. P. Murty, J. E. Dunsmoor, E. A. Phelps, L. Davachi, Reward retroactively enhances memory consolidation for related items. *Learn. Mem.* **24**, 65–69 (2017).
76. L. A. Atherton, D. Dupret, J. R. Mellor, Memory trace replay: The shaping of memory consolidation by neuromodulation. *Trends Neurosci.* **38**, 560–570 (2015).
77. D. J. Palombo, S. Sheldon, B. Levine, Individual Differences in Autobiographical Memory. *Trends Cogn. Sci.* **22**, 583–597 (2018).
78. A. Richardson, *Individual Differences in Imaging: Their Measurement, Origins, and Consequences* (Routledge, 2020).
79. A. H. Sinclair, S. Hakimi, M. L. Stanley, R. A. Adcock, G. R. Samanez-Larkin, Pairing facts with imagined consequences improves pandemic-related risk perception. *Proc. Natl. Acad. Sci. U.S.A.* **118**, e2100970118 (2021).
80. D. L. Schacter, D. R. Addis, R. L. Buckner, "Episodic simulation of future events: Concepts, data, and applications" in *The Year in Cognitive Neuroscience 2008*, Annals of the New York Academy of Science (Blackwell Publishing, 2008), pp. 39–60.
81. S. A. Rösch, D. F. Stramaccia, R. G. Benoit, Promoting farsighted decisions via episodic future thinking: A meta-analysis. *J. Exp. Psychol. Gen.* **151**, 1606–1635 (2022).
82. D. L. Schacter, R. G. Benoit, K. K. Szpunar, Episodic future thinking: Mechanisms and functions. *Curr. Opin. Behav. Sci.* **17**, 41–50 (2017).
83. M. A. Neroni, N. Gamboz, M. A. Brandimonte, Does episodic future thinking improve prospective remembering? *Conscious. Cognit.* **23**, 53–62 (2014).
84. Stan Development Team, RStan: The R interface to Stan (2022).
85. A. Vehtari, A. Gelman, J. Gabry, Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Stat. Comput.* **27**, 1413–1432 (2017).
86. L. Danwitz, D. Mathar, E. Smith, D. Tuzsus, J. Peters, Parameter and model recovery of reinforcement learning models for restless bandit problems. *Comput. Brain Behav.* **5**, 547–563 (2022).
87. A. H. Sinclair, Y. C. Wang, R. A. Adcock, Instructed Motivational States Bias Reinforcement Learning and Memory Formation. Open Science Framework. https://doi.org/10.17605/OSF.IO/7SZ23 (Accessed 23 March 2023).
88. A. H. Sinclair, Y. C. Wang, R. A. Adcock, Preregistration: Instructed Motivational States Bias Reinforcement Learning and Memory Formation. Open Science Framework. https://doi.org/10.17605/OSF.IO/FTQKR (Accessed 9 February 2023).